

## Enhancing turbine gear fault monitoring through the integration of envelope analysis and recurrent neural networks

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**Abstract.** Gearbox is an integral part of wind turbine (WT) design and timely fault detection can reduce unexpected downtime and maintenance costs. This study presents a method to detect turbine gear faults that combines Envelope analysis combines with Gated Recurrent Units (GRUs). Envelope analysis extracts high-frequency fault features from vibration signals, while GRUs excel in recognizing temporal patterns, making this combination particularly powerful for early fault detection in gears. This method aims to enhance diagnostic accuracy, offering significant advantages over traditional methods that rely primarily on human inspection and basic signal processing. Its ability to detect and localize issues early ensures a direct and impactful contribution to optimizing maintenance strategies. The results, based on the analysis of signals from a planetary gearbox, demonstrate a marked improvement in diagnostic capabilities.

**Keywords:** gated recurrent units; gear faults; envelope analysis; recurrent neural networks; vibration signals

### 1. Introduction

Wind turbines are an important source of power generation due to their efficiency and reliability. WTs are essentially composed of several subsystems, with the gearbox playing an important role in transferring power from the rotor hub to the generator (Pichika *et al.* 2022). Many components are susceptible to unexpected failures due to highly unpredictable and extreme weather conditions, ranging from calm to intense winds, tropical heat over long periods of time (Zhang *et al.* 2023). Studies indicate that gearbox failures occur less frequently than issues with other turbine components; however, downtime due to gearbox failure is higher compared to other components (Bai *et al.* 2024). If these deficiencies are not detected and corrected early, they can reduce productivity and degrade system performance. Under such extreme circumstances, it is important to ensure continuous operation and reliability of WTs to maintain energy production and minimize downtime. (Sharma and Anand 2016, Djaballah *et al.* 2023).

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As manufacturing technologies progress, predicting machine life are essential to improve performance (Sun and Wang 2024). Identifying faults at an early stage is essential, as unnoticed failures can lead to rapid deterioration and expensive downtime. Various condition-monitoring techniques, particularly vibration analysis, are used to detect gearbox faults (Tang *et al.* 2023).

Recently, there has been renewed interest in using deep learning (DL) techniques for gearbox condition monitoring, as these methods can automatically extract deep features from vibration signals through end-to-end processing (Zheng *et al.* 2024). Generally, existing deep learning models commonly utilize Convolutional Neural Networks (CNNs) to extract spatial features, while recurrent neural networks (RNNs) are used to capture temporal features. For example, (Fu *et al.* 2019) introduced a normal behavior modelling method to monitor WT gearboxes, which combines CNNs for spatial feature extraction and Long Short-Term Memory (LSTM) networks for capturing temporal features. Meanwhile, other research has concentrated on the temporal correlation of data, using temporal feature extraction for condition monitoring. For example, (Su *et al.* 2022) proposed a novel condition monitoring method for offshore WT gearboxes using spatial-temporal attention and a GRU network and provided model interpretability through attention weights. (Qian *et al.* 2019) used an LSTM model to analyze the time-based correlations in SCADA time-series data.

This study introduces a novel method that combines envelope analysis and RNN to detect gear faults. Envelope analysis effectively extracts fault information from vibration signals by analyzing the surface separation features of gear fault bonds. In parallel, RNN, especially GRU, excels in detecting and understanding relationships and patterns in time series data, making it ideal for diagnosing gear faults (Zhu *et al.* 2024). The proposed seeks to increase efficiency of gear problem analysis by combining the advantages of envelope analysis and RNN. This research aims to establish a robust and effective gear fault diagnosis system. This system can provide early warning and enable faster maintenance (Tianhao *et al.* 2024). The limited availability of training data poses a significant challenge in the systematic evaluation of effective gear fault detection algorithms. Traditional gear fault diagnosis models often struggle to achieve high accuracy and efficiency when training data are insufficient (Beldjaatit *et al.* 2023). To address this problem, the proposed method capitalizes on the strengths of gated RNNs for efficient feature extraction (Liu *et al.* 2020) (Hechifa *et al.* 2023). The proposed method can detect new gear failures faster (Kumar *et al.* 2020), while maintaining the original detection capability. The proposed gear fault detection method is assessed using experiments using test signals obtained from a planetary gearbox, confirming the practical. The results demonstrate the efficacy of the proposed approach, including exceptional analysis accuracy, fast detection speed and real-time fault detection Envelope analysis with characteristic units.

The first step is to divide the raw vibration signal into smaller sub-signals. In the second step, the envelope spectrum of each individual sub-signal is calculated. Then, a GRU classifier is applied to learn from the data and identify faults. By exploiting the GRU's memory and time-dependence features, it can effectively capture sequence patterns in gear vibration data and predict the occurrence of gear faults with high accuracy. Furthermore, the method offers fault recovery insights at each level of the analysis.

The principal contributions can be summarized as follows:

- We introduce a hybrid approach combining envelope analysis and GRU, with the aim of improving the accuracy and efficiency of gear fault diagnosis in WT gearboxes.
- Envelope analysis is employed to filter and extract characteristic fault features from vibration signals, thereby enhancing the accuracy of gear fault identification.
- The GRU model is used to capture time dependencies and sequential patterns in vibration

data, enhancing the detection speed and precision of gear faults.

The paper is structured into three main sections. Section 'Experimental materials and methods' provides a description of the methodology, and the dataset used for the study is described. Section 'Results and discussion' offers an analysis and interprets the results obtained. Finally, section 'Conclusions' concludes the paper and provides a summary and suggests directions for future research.

## 2. Experimental materials and methods

### 2.1 Proposed method

The research methodology used in the present study is shown in Fig. 1 and follows a hybrid approach with three main steps. The raw vibration signal is first segmented into smaller sub-signals. The envelope spectrum of each individual sub-signal is computed in the second step. Afterwards, GRU is employed as a classifier to learn from the data and identify faults. Through its ability to capture temporal dependencies and utilize memory, the GRU effectively identifies sequential patterns in the gear vibration data, enabling accurate prediction of gear issues, as shown in Fig. 1. Furthermore, the proposed approach facilitates the systematic extraction of fault characteristics at each layer of deep learning, resulting in enhanced precision in detecting various types of gear defects.

In our methodology, short-term memory plays a crucial role in effectively detecting and diagnosing gear faults, especially in systems where fault characteristics may evolve over time or occur intermittently. The short-term memory component is implemented through the use of Gated Recurrent Units. The GRU's architecture allows it to capture temporal dependencies in sequential

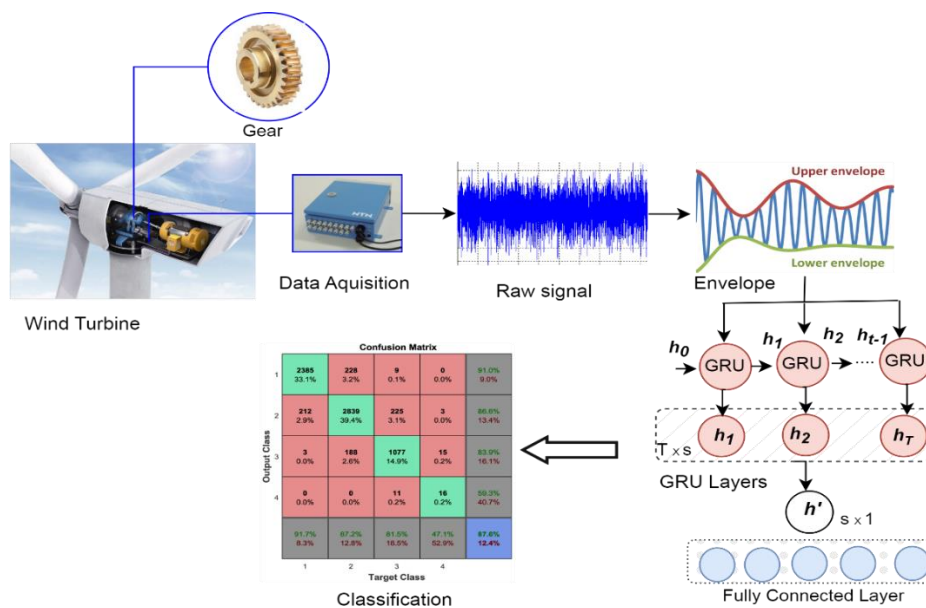


Fig. 1 Flowchart of the suggested fault diagnosis method

data, which is particularly important for gear vibration signals. These signals can show subtle changes that might only be visible over a short time span, making it essential to retain past information for accurate fault detection. By utilizing short-term memory, the GRU can remember key features from previous time steps while disregarding irrelevant data, thus focusing on the most significant parts of the signal that indicate potential faults.

This mechanism allows the system to better recognize and predict faults that may not be immediately obvious from a single snapshot of the data but require the model to analyze the progression of vibrations over a short window. For example, gear faults like cracks or wear typically develop incrementally, and the GRU's ability to remember recent patterns enables it to identify these gradual changes, as they emerge, leading to early and more precise fault detection.

This ability to capture and leverage temporal patterns improves the diagnostic accuracy and speed of our method, ensuring that it can detect potential gear faults well before they lead to significant damage or failure.

## 2.2 Envelope analysis (EA)

EA is an essential approach widely applied in the diagnosis of machine rotary fault (Tyagi and Panigrahi 2017). It serves a crucial function in the contextual information in unprocessed time-based signals, thus facilitating the detection of fault signals indicating gear damage. If the envelope analysis method is systematic it is used for accurate programming aimed at converting the original signal into a form suitable for error detection and estimation. Initially, a bandpass filter is deliberately applied to the raw signal, focusing on the resonant frequency of the device (Sally and Dai 2003). The aim of this method is to remove irrelevant features beyond normal frequencies, so the relevant characteristics of gear errors can be extracted followed by calculating the envelope of the signal by applying a Hilbert transform role in the envelope extraction step. This method enables the separation of a complex signal from the actual original signal, where the conceptual component represents a phase-inverted portion of the signal. The time-frequency properties of the signal are mathematically masked by specific equations so does this change.

The Hilbert transform is a technique used to convert a real signal into an analytic signal in the time domain. (Eq. (1)) represents the Hilbert transform, while (Eq. (2)) describes the inverse transformation. In envelope analysis, the Hilbert transform is applied to the real signal  $x(t)$ , resulting in a transformed signal  $\hat{x}(t)$ . The analytic signal is then constructed a  $z(t) = x(t) + j\hat{x}(t)$ , where the real part is the original signal, and the imaginary part is the Hilbert-transformed version of the signal. The magnitude of this analytic signal represents the envelope of the real signal, capturing its amplitude modulation.

$$\hat{x}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (1)$$

$$x(t) = -\frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\hat{x}(\tau)}{t-\tau} d\tau \quad (2)$$

Envelope analysis for fault detection in mechanical systems, such as gear monitoring, involves a structured four-step process: First, the filtered signal is obtained by applying a high-pass or band-pass filter to the raw vibration signal to isolate the frequency bands associated with faults. Next, the Hilbert Transform is applied to this filtered signal, creating an analytic signal that combines both the original signal and its phase-shifted version, capturing instantaneous frequency and phase information. Then, the envelope signal is extracted by calculating the magnitude of this

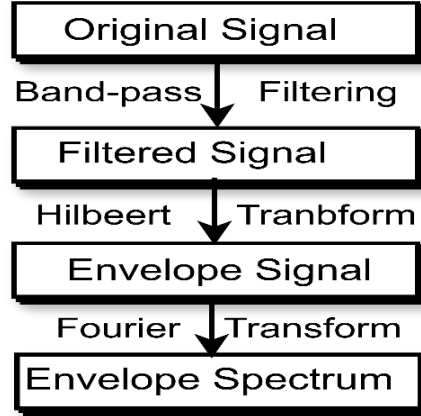


Fig. 2 Signal process of envelope analysis

analytic signal, emphasizing amplitude modulations that are indicative of faults like wear or damage. Finally, the envelope spectrum is generated by applying a Fast Fourier Transform (FFT) to the envelope signal, allowing for the identification of fault-related frequencies and modulation patterns, which are then analyzed to pinpoint specific faults in the system. The steps of the application of this technique are demonstrated in Fig. 2.

### 2.3 Gated Recurrent Unit (GRU)

GRU is a powerful modification of the conventional RNN that uses a joint gating mechanism similar to Long Short-Term Memory (LSTM) (Djaballah *et al.* 2024) to overcome short-term memory problems. The update gate applies a sigmoid function to the input  $xt$  and the preceding hidden layer output  $ht - 1$  in order to determine which information should be kept. The GRU cell structure incorporates two gate functions: the update gate  $zt$  and the reset gate  $rt$ . The LSTM architecture simplifies the update gate by merging it with the input gate and the forgetting gate. This process involves mixing and modifying the original cell state and hidden state. Changing the status information of the GRU unit follows this procedure: The  $ht - 1$  from the previous time step is forwarded to the current time step through the  $zt$ . The extent to which the previous  $ht - 1$  affects the current layer is managed by the update gate value Fig. 3. The current input  $ht - 1$  and  $zt$  are written into the current candidate hidden state  $ht$ , where the influence of  $ht - 1$  is regulated by the reset gate  $rt$ , and the value of  $rt$  is reset (Su *et al.* 2022).

The relationships among the variables can be described as follows:

$$zt = \sigma(Wz * [ht - 1, xt]) \quad (3)$$

$$rt = \sigma(Wr * [ht - 1, xt]) \quad (4)$$

$$ht = \tanh(W * [rt * ht - 1, xt]) \quad (5)$$

$$ht = \tanh(W * [rt * ht - 1, xt]) \quad (6)$$

$Wz$ ,  $Wr$ , and  $W$  are the update gate weight, reset gate weight, and weight coefficient, respectively.

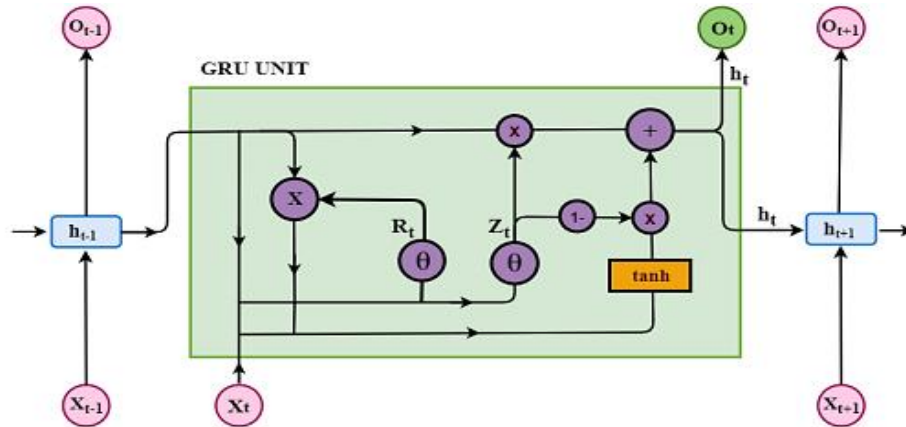


Fig. 3 Feedforward and Backward Propagation in GRU

The ReLU activation function, with a range of  $[0 - 1]$ , is applied; \* indicates the inner product of the vectors.

#### 2.4 Dataset gearbox description

The Southeastern University Gearbox Fault Diagnostic Dataset provides useful insight into the performance and status of gear systems. To ensure the accuracy and reliability of the testing process, as shown in Fig. 4 (Ma 2021), the dataset was collected correctly using the Drivetrain Dynamic Simulator. It includes a driving motor, a speed regulator, a planetary gearbox, a parallel gearbox, a brake device, and a brake regulator. This study examines the gear fault sub-dataset, which is part of a larger dataset including bearing and gear data. The goal is to explore the particular details of gear degradation. The gear fault sub-dataset provides an extensive examination of many types of faults, such as overall health, cracks at the base of the tooth, absence of one tooth in the gear, cracks at the base of the tooth root, and wear on the tooth surface, as listed in Table 1. These fault categories are essential indicators of possible gear failures and are useful for improving predictive maintenance procedures.

The dataset records the dynamic performance of the gear system under various operating conditions, specifically at two different combinations of rotational speed and system load: '20 Hz and 0 V' and '30 Hz and 2 V' (Habbouche *et al.* 2021). In our study, we used '20 Hz and 0 V'. The data are carefully curated, comprising signals obtained from eight strategically positioned sensors to capture various aspects of the gear system's behavior. The sensor data comprise vibrations captured from several angles (model: 608A11, sample frequency: 5120 Hz); one is mounted on the surface of the motor to measure the z-axial vibration signal of the motor (F1), as well as vibrations in the X, Y, and Z axes of the planetary gearbox (F2). In addition, sensors six and seven detect vibrations emanating from the parallel gearboxes (F3), while sensor eight provides information on vibrations in the X, Y, and Z axes (Liu and Long 2020), as shown in Fig. 5.

This study employs a scaled model to simulate the dynamic behaviors of gearboxes in wind turbine systems for the purpose of fault detection and diagnostic analysis. By utilizing a scaled

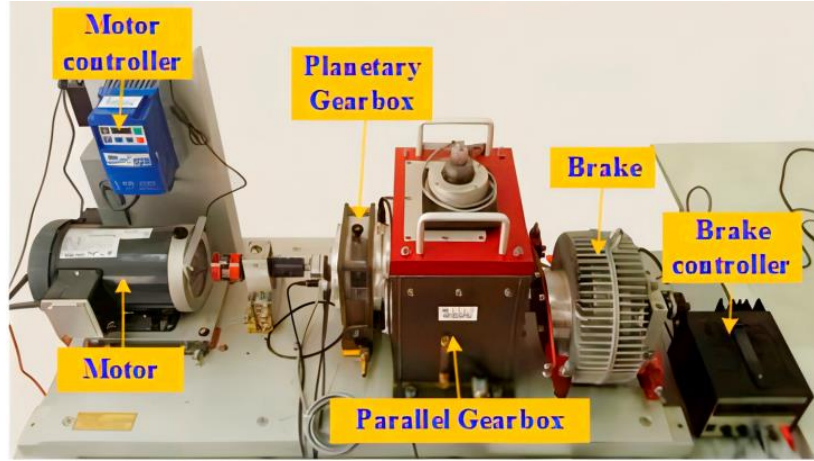
Fig. 4 Test rig gearbox. (Huo *et al.* 2022)

Table 1 Description of the dataset gearbox

Type	Description	Training samples	Testing samples	Target value
Health	Healthy Gear	2400	1600	1
Chipped	Chipped Cracks in the gear feet	2400	1600	2
Miss	Missing one of feet in the gear	2400	1600	3
Crack	Cracks at the root of the tooth	2400	1600	4
Surface	Surface Wear on gear surfaces	2400	1600	5

model, we are able to isolate and investigate specific fault features under controlled conditions, allowing for a more focused analysis of the proposed fault detection method. The scale of the model was chosen to reflect critical dynamic characteristics of the gearbox, such as vibrational modes and fault propagation, which are crucial for accurate fault detection.

### 2.5 Performance measurement

The performance of each classification model is evaluated by using statistical measures. The measures defined by false positives (FP), false negatives (FN), true negatives (TN), and true positives (TP), where P and N represent the positive and negative samples in the original dataset. All the statistical measures are represented as a percentage in the following equations

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (7)$$

$$Specificity = \frac{TN}{FP+TN} \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$F1 - score = 2 \times \frac{precision \times sensitivity}{precision+sensitivity} \quad (10)$$

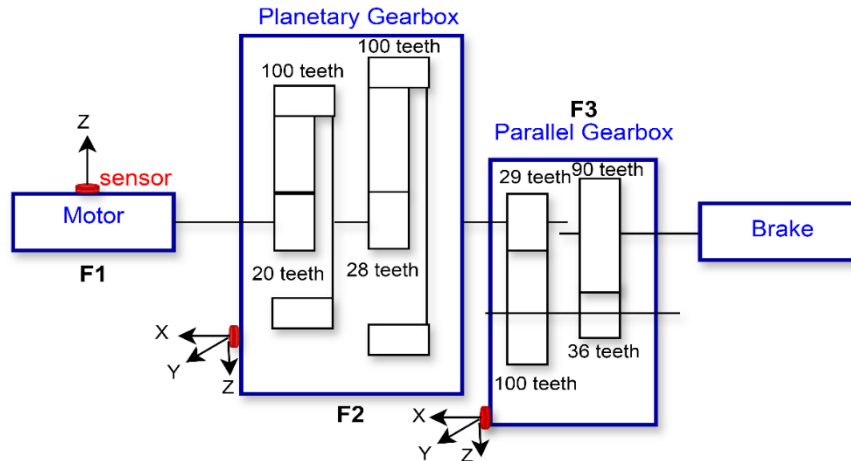


Fig. 5 Schematic Diagram of Gearbox System

### 3. Results and discussion

Figs. 6 and 7 present a comparative analysis of signal envelopes from gear systems exhibiting normal state and crack fault. The analysis is depicted in time domains to illustrate the distinct characteristics of gear signals under varying operational conditions.

In the time domain Fig. 8(a), two graphs compare the envelope signals of a healthy gear (top panel) and a gear with a crack (bottom panel). Each graph illustrates three superimposed signal traces: the raw signal (blue), the upper envelope (red), and the lower envelope (orange). For the healthy gear, the envelope signals are more tightly bound and exhibit less variance than those of the cracked gear, indicating a more stable and consistent gear operation. In contrast, the envelope signals for the cracked gear show a greater deviation between the upper and lower envelopes, suggesting increased signal irregularities due to the presence of gear faults.

A fast Fourier transform (FFT) analysis of the envelope signal is presented in the frequency domain, as shown in Fig. 8(b). The healthy FFT envelope graph reveals a relatively clean spectral signature with few strong frequencies and low-amplitude harmonic content, indicating that the gear system is in good condition, with little to no erosion or damage. In contrast, the 'Crack FFT envelope' exhibits a more complex frequency spectrum with many significant frequencies and high harmonic content, suggesting possible faults or damage in the gear system.

The visual comparison underscores the effectiveness of envelope signal analysis in detecting and differentiating the conditions of gear systems. The upper and lower envelope signals in the time domain and the harmonic content in the frequency domain serve as critical indicators of gear health. This analysis could be further leveraged to develop predictive maintenance schedules and prevent gear system failures through early detection of anomalies.

The time window (0.5 second) was chosen for segmenting the signal in the envelope analysis to strike a balance between time and frequency resolution. This choice allows for the detection of fast, transient faults, which are common in mechanical failures or sudden impacts. Given the sampling rate of 20,000 Hz, this window is short enough to capture high-frequency oscillations while still

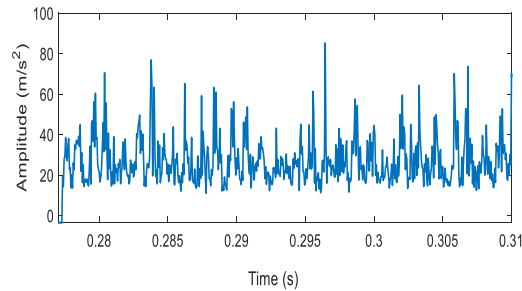


Fig. 6 Vibration signals of normal state

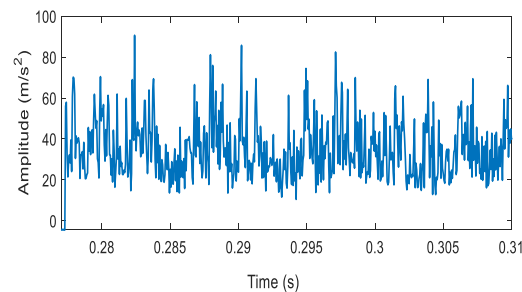


Fig. 7 Vibration signals of crack fault

providing adequate frequency resolution. Although shorter windows may result in broader spectral peaks, the 0.5 second interval is effective for identifying rapid changes in the signal that would be lost with longer periods. Longer windows could improve frequency resolution, but they would diminish the ability to detect quick, transient events. This time window selection optimizes the performance for fast-moving anomalies while preserving acceptable frequency clarity.

### 3.1 Comparison of two kinds of input data

In testing the effectiveness of envelope analysis in gear fault classification tasks, the performance of the GRU neural network was evaluated using two different sets of input data: (1) the original signal data, and (2) the envelope spectrum data. The GRU models, corresponding to each data type, were subjected to a training regimen spanning 400 epochs.

Fig. 9 shows the improvement of the training accuracy of the two models throughout the training epochs. Notably, modelling using envelope-spectrum data reached an impressive accuracy of 92% after 400 epochs of training, and this accuracy stagnated at around 96% after the 300 epoch mark. In contrast, models trained with the original signal data showed a comparatively slow learning curve, requiring approximately 270 epochs to attain an 80% accuracy threshold. This juxtaposition of training dynamic highlights the superior learning efficiency of the GRU when furnished with envelope spectrum data. The data indicates a significant reduction in the number of epochs required to reach an advanced level of accuracy, thus suggesting that envelope analysis serves as a potent feature extraction method, enhancing the GRU's ability to classify gear faults with greater expediency and fewer computational iterations.

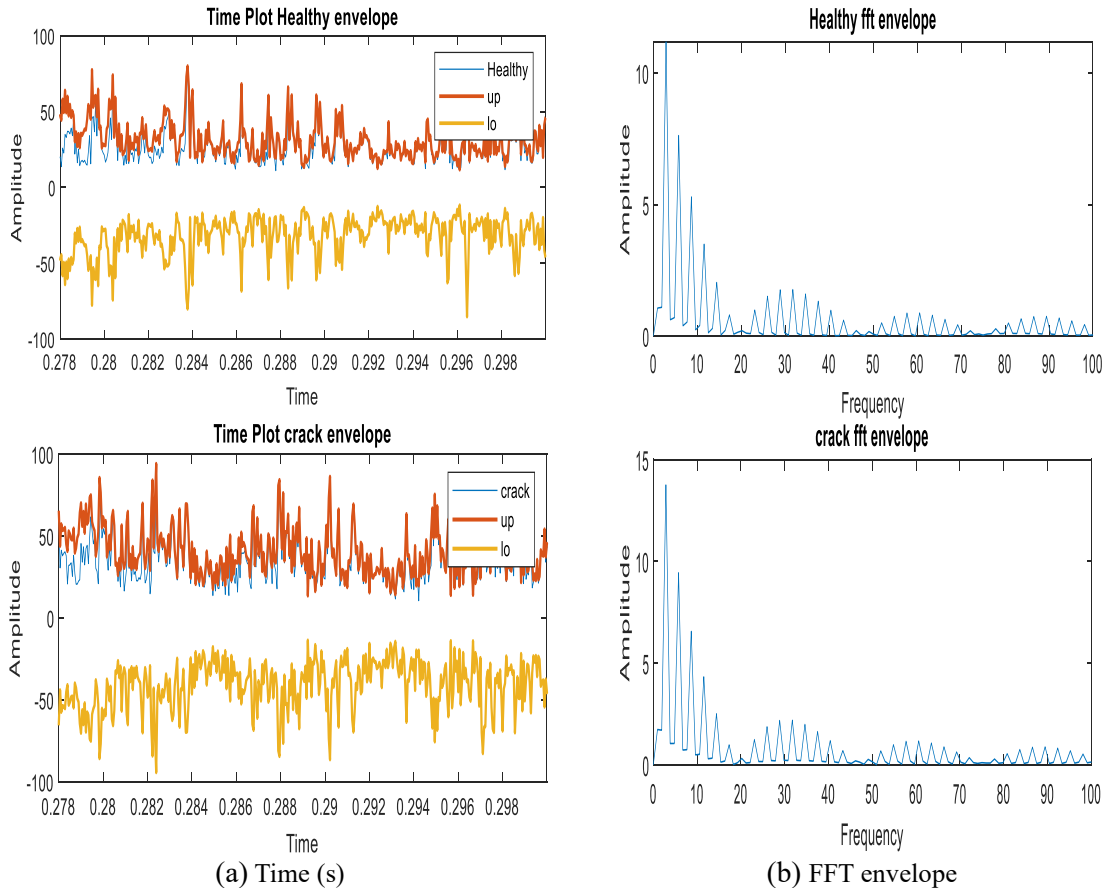


Fig. 8 Comparative Analysis of Envelope Signal Characteristics in Healthy and Faulty Gear Systems

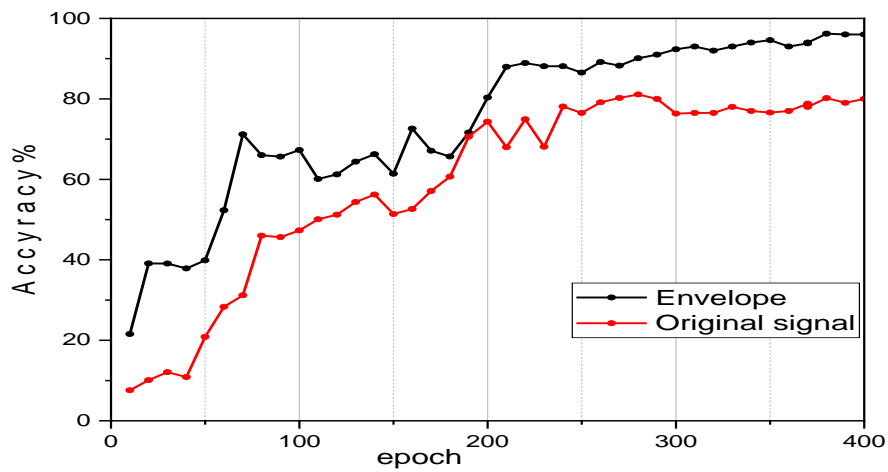


Fig. 9 Performance of GRU

Table 2 Architecture of GRU

Layer	Name
	Input -
1	GRU Activation(tanh)
2	GRU Activation(tanh)
3	Dropout (0.5)
4	Fully connected
	Output (SoftMax)

		Prediction Class				
		Healthy	Chipped	Missing	Cracks	Surface Wear
Actual Class	Healthy	1340	200	3	1	27
	Chipped	221	1370	12	3	1
	Missing	4	34	1495	75	0
	Cracks	5	4	37	1519	0
	Surface Wear	39	2	0	0	1592

Fig. 10 Confusion matrix of the hybrid model

Table 3 Performance of proposed method

Condition Types	Accuracy rate in testing dataset (%)	
	GRU	EA + GRU
Healthy Gear	84.58	98.89
Chipped Cracks	85.66	92.45
Missing	74.57	94.83
Cracks	78.66	91.75
Surface Wear	76.77	95.89
Average	80.05	94.78

The final classification results of five condition types listed above can be obtained, as presented in Table 3 and Fig.10. Two distinct GRU models were compared: one trained with the original dataset and the other with an envelope analysis processed dataset.

The GRU model utilizing the original dataset achieved an accuracy rate of 80.05% on the testing dataset. This baseline performance is commendable, demonstrating the ability of the model

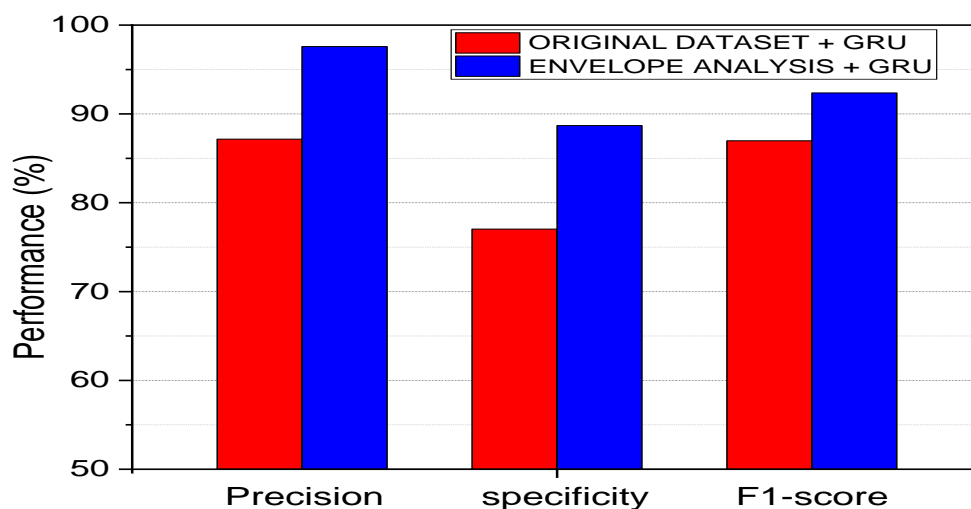


Fig. 11 Performance results of each input data of GRU

to learn and make predictions from raw data. However, the second model, which included envelope analysis pre-processing and GRU, performed better than the first model with a significantly higher accuracy rate of 94.78%.

The 14.73% increase in accuracy in envelope analysis indicates that this method of signal processing successfully extracts relevant features from the raw data that are more informative for the GRU model. This indicates that envelope analysis can have worked out a good pre-processing step in gear fault classification.

The reason for the improved performance may be the ability of envelope analysis to enhance the quality of the signal associated with gear faults, thereby increasing the model's ability to discriminate between commonly faulty conditions. Thus, this finding highlights the potential of advanced signal processing techniques to enhance the machine learning model effective efforts in predictive maintenance.

Fig. 11 shows the performance metrics (specificity, F1-score and precision) for GRU's two inputs: raw data and EA. Specificity, specificity, and F1-score improve significantly with input envelope analysis at GRU, close to 97%, 88.96%, and 93.03%, respectively. These significant increases indicate that the envelope analysis method provides more accurate predictive power in the model is enhanced. By reducing noise, this study highlights the potential of envelope analysis as a valuable tool to enhance the performance of ML models, and thus makes a strong case for using will be involved in assessment and forecasting processes.

For further explore the feature learning process of the hybrid model, the t-SNE is used to visualize the high-dimensional feature representations learned by each layer of the GRU, as shown in Fig. 12.

Fig. 12(a) indicates the features of the input test samples for the five operating conditions of the gearbox. In Fig. 12(b), after passing through the first hidden layer, the input data is transformed, and the features are projected into a new representation. Fig. 12(c) shows how the representations are further processed. By this stage, the features are more abstract, producing increasingly clear boundaries between different types of faults. In Fig. 12(d), the fully connected layer ensures that points in the same category are clustered together so that they can be easily distinguished by

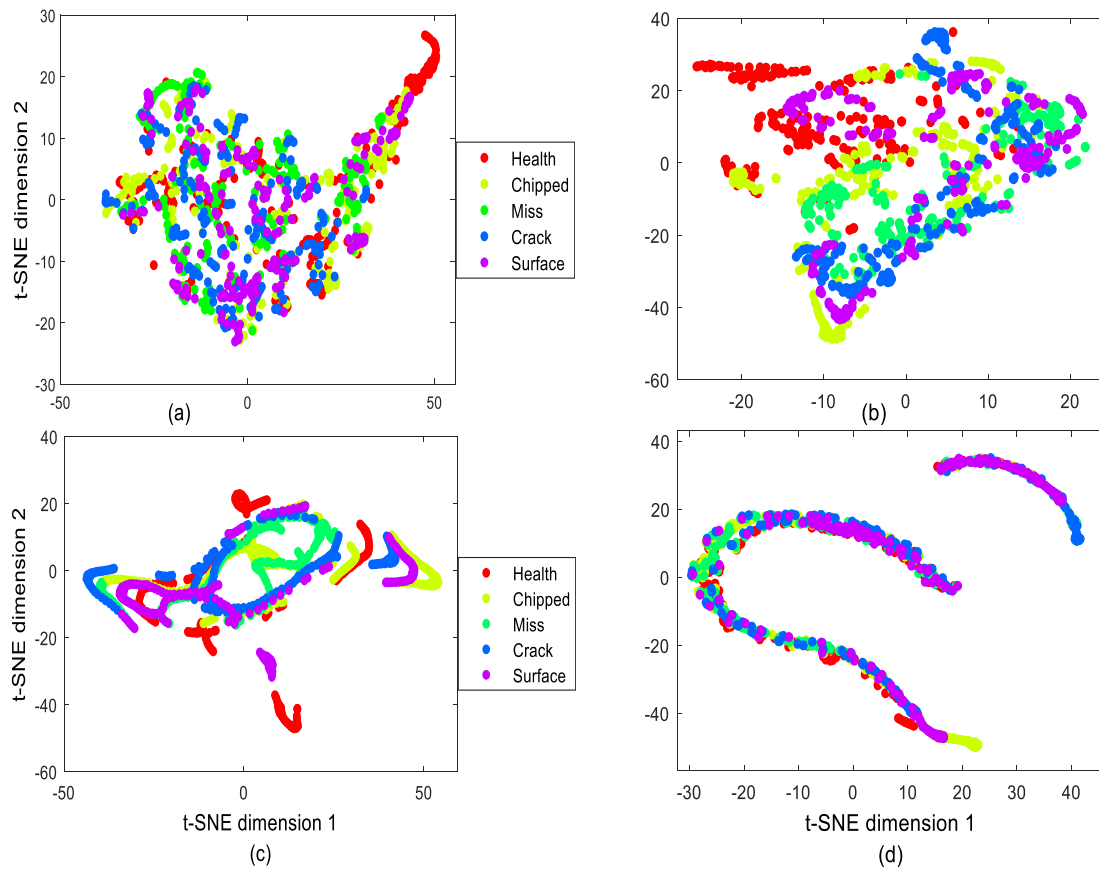


Fig. 12 Feature visualization based on t-SNE (a) Input layer, (b) output of the first layer, (c) output of the second layer and (d) output of the second fully connected layer

Table 4 A comparative analysis of the accuracy of the proposed method and other literature sources

Literature	Models	Accuracy (%)
Malik <i>et al.</i> (2019)	EMD + ANN	73
Durbhaka <i>et al.</i> (2021)	LSTM + Cuckoo	87.5
Lixiao <i>et al.</i> (2019)	SVM	76.50
Zheng <i>et al.</i> (2022)	BiGRU	93.80
Our proposed model	Envelope Analysis + GRU	94.78

means of the classifier. Thus, the feasibility of our model is demonstrated for fault diagnosis and feature extraction.

Table 4 displays a comparison of the results of the proposed method with other gear fault diagnostic methods on the gearbox dataset. Malik *et al.* (2019) propose an Empirical Mode Decomposition (EMD) for feature extraction and an Artificial Neural Network (ANN) for classification, achieving an accuracy of 73%. Durbhaka *et al.* (2021) present a model combining

LSTM networks with a Cuckoo Search algorithm for fault diagnosis, achieving a successful classification with 87.5% accuracy. Lixiao *et al.* (2019) used a support vector machine (SVM), which achieved an accuracy of 76.5%. Another study (Zheng *et al.* 2022) used binary GRU (BiGRU), achieving 93.8% accuracy. Our proposed model combines Envelope Analysis with GRU, which has achieved the highest accuracy of 94.78%. Each method uses machine learning techniques and signal processing techniques and shows the trend of combining advanced neural network algorithms to improve the analysis accuracy in gear fault detection.

## 5. Conclusions

Advanced diagnostic techniques must be used to identify faults, avoid failures, and ensure proper operation of the WT, identify gearbox faults, enable timely maintenance, and reduce the chances of unexpected downtime. This study introduces a hybrid approach for gear fault diagnosis in WT gearboxes by combining EA and GRU-based classification. The main objective was to improve the accuracy of fault detection, overcoming the limitations of traditional methods that rely on basic signal processing and human inspection. The results indicate that the proposed model significantly surpasses traditional techniques in both diagnostic accuracy and efficiency. Through the integration of envelope analysis and GRUs, relevant fault features were extracted from vibration signals and classified using the GRU's temporal pattern recognition capabilities. Envelope analysis effectively filtered out irrelevant noise, allowing for more precise identification of gear faults. The GRU model, when trained on envelope-spectrum data, achieved an impressive classification accuracy of 94.78%. The experimental results using the southeastern university gearbox fault diagnostic dataset validated the effectiveness of the proposed model. These findings underscore the potential of combining advanced signal processing techniques with deep learning architectures for predictive maintenance, offering a significant leap toward real-time, accurate fault detection in WT gearboxes.

Despite the strengths of the proposed method, there are some limitations that should be addressed in future research. Future work will validate these findings using real gearboxes, enhancing the alignment between scaled model simulations and practical applications. This will ensure the methodology's applicability across various machinery types and in conjunction with other predictive maintenance technologies, thereby expanding its utility and impact in industrial maintenance.

## References

- Bai, X., Han, S., Kang, Z., Tao, T., Pang, C., Dai, S. and Liu, Y. (2024), "Wind turbine gearbox oil temperature feature extraction and condition monitoring based on energy flow", *Appl. Energ.*, **371**, 123687. <https://doi.org/10.1016/j.apenergy.2024.123687>.
- Beldjaatit, C., Sebbagh, T. and Guentri, H. (2023), "Discrete wavelet transform and energy distribution for effective bearing fault detection and analysis", *Przeglad Elektrotechniczny*, **99**(7). <https://doi.org/10.15199/48.2023.07.05>.
- Cao, L., Zheng, Q., Hamidreza, Z., Zhenkai, H. and Fanghong, Z. (2019), "Fault diagnosis of wind turbine gearbox based on deep bi-directional long short-term memory under time-varying non-stationary operating conditions", *IEEE Access*, **7**, 155219-155228. <https://doi.org/10.1109/ACCESS.2019.2947501>.
- Djaballah, S., Kamel, M., Khaled, K. and Mounir, S. (2023), "Deep transfer learning for bearing fault

- diagnosis using CWT time–frequency images and convolutional neural networks”, *J. Fail. Anal. Prevent.*, **23**(3), 1046-1058. <https://doi.org/10.1007/s11668-023-01645-4>.
- Djaballah, S., Lotfi, S., Kamel, M., Hechifa, A., Mohit, B. and Ievgen, Z. (2024), “A hybrid LSTM random forest model with grey wolf optimization for enhanced detection of multiple bearing faults”, *Scientific Reports*, **14**(1), 23997. <https://doi.org/10.1038/s41598-024-75174-x>.
- Du, X., Xiaohui, D. and Fan, T. (2023), “Network security situation prediction based on optimized clock-cycle recurrent neural network for sensor-enabled networks”, *Sensors*, **23**(13), 6087. <https://doi.org/10.3390/s23136087>.
- Durbhaka, G., Barani, S., Mamta, M., Tanzila, S., Amjad, R. and Lalit, M. (2021), “Swarm-LSTM: Condition monitoring of gearbox fault diagnosis based on hybrid LSTM deep neural network optimized by swarm intelligence algorithms”, *CMC-Comput. Mater. Continua*, **66**(2), 2041-2059. <https://doi.org/10.32604/cmc.2020.013131>.
- Fu, J., Chu, J., Guo, P. and Chen, Z. (2019), “Condition monitoring of wind turbine gearbox bearing based on deep learning model”, *IEEE Access*, **7**, 57078-57087. <https://doi.org/10.1109/ACCESS.2019.2912621>.
- Habbouche, H., Benkedjouh, T., Amirat, Y. and Benbouzid, M. (2021), “Gearbox failure diagnosis using a multisensor data-fusion machine-learning-based approach”, *Entropy*, **23**(6), 697. <https://doi.org/10.3390/e23060697>.
- Hechifa, A., Abdelaziz, L., Chouaib, L. and Arnaud, N. (2023), “The effect of source data on graphical pentagons DGA methods for detecting incipient faults in power transformers”, *Proceedings of the Int Conference on the Decision Aid Sciences and Applications*, Algeria. <https://doi.org/10.1109/DASA59624.2023.10286665>.
- Huo, D., Yuyun, K., Baiyang, W., Guifang F., Jiawei, Z. and Hongrui, Z. (2022), “Gear fault diagnosis method based on multi-sensor information fusion and VGG”, *Entropy*, **24**(11), 1618. <https://doi.org/10.3390/e24111618>.
- Kumar, A., Gandhi, C.P., Zhou, Y., Kumar, R. and Xiang, J. (2020), “Latest developments in gear defect diagnosis and prognosis: A review”, *Measurement*, **158**, 107735. <https://doi.org/10.1016/j.measurement.2020.107735>.
- Liu, F., Jingzhong, Z., Lailei, Z. and Cheng, C.H. (2020), “Combining attention-based bidirectional gated recurrent neural network and two-dimensional convolutional neural network for document-level sentiment classification”, *Neurocomput.*, **371**, 39-50. <https://doi.org/10.1016/j.neucom.2019.09.012>.
- Liu, Z. and Long, Z. (2020), “A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings”, *Measurement*, **149**, 107002. <https://doi.org/10.1016/j.measurement.2019.107002>.
- Ma, J. (2021), “Research on life prediction of fan spindle bearing based on gated recurrent unit neural network”, *In E3S Web of Conferences*, **261**, 01039. <https://doi.org/10.1051/e3sconf/202126101039>.
- Malik, H., Yogesh, P., Aakash, P. and Rajneesh, S. (2019), “Feature extraction using EMD and classifier through artificial neural networks for gearbox fault diagnosis, In Applications of Artificial Intelligence Techniques in Engineering”, *SIGMA Springer Singapore*, **2**, 309-317. [https://doi.org/10.1007/978-981-13-1822-1\\_28](https://doi.org/10.1007/978-981-13-1822-1_28).
- McInerny, S.A. and Dai, Y. (2003), “Basic vibration signal processing for bearing fault detection”, *IEEE T. Education*, **46**(1), 149-156. <https://doi.org/10.1109/TE.2002.808234>.
- Pichika, S., Meganaa, G., Geetha, S. and Malapati, A. (2022), “Multi-component fault classification of a wind turbine gearbox using integrated condition monitoring and hybrid ensemble method approach”, *Appl. Acoust.*, **195**, 108814. <https://doi.org/10.1016/j.apacoust.2022.108814>.
- Qian, P., Tian, X., Kanfoud, J., Lee, J.L.Y. and Gan, T.H. (2019). “A novel condition monitoring method of wind turbines based on long short-term memory neural network”, *Energies*, **12**(18), 3411. <https://doi.org/10.3390/en12183411>.
- Sharma, V. and Anand, P. (2016), “A review of gear fault diagnosis using various condition indicators”, *Procedia Eng.*, **144**, 253-263. <https://doi.org/10.1016/j.proeng.2016.05.131>.
- Su, X., Shan, Y., Li, C., Mi, Y., Fu, Y. and Dong, Z. (2022), “Spatial-temporal attention and GRU based interpretable condition monitoring of offshore wind turbine gearboxes”, *IET Renew. Power Generation*,

- 16(2), 402-415. <https://doi.org/10.1049/rpg2.12336>.
- Sun, Y. and Wang, W. (2024), "Role of image feature enhancement in intelligent fault diagnosis for mechanical equipment: A review", *Eng. Fail. Anal.*, **156**, 107815. <https://doi.org/10.1016/j.engfailanal.2023.107815>.
- Tang, X., Xu, Y., Sun, X., Liu, Y., Jia, Y., Gu, F. and Ball, A.D. (2023), "Intelligent fault diagnosis of helical gearboxes with compressive sensing based non-contact measurements", *ISA Trans.*, **133**, 559-574. <https://doi.org/10.1016/j.isatra.2022.07.020>.
- Tianhao, W., Hongying, M., Rui, Q., Zhang, F. and Asoke, K. (2024), "Real-Time Monitoring of Wind Turbine Bearing Using Simple Neural Network on Raspberry Pi", *Appl. Sci.*, **14**(7), 3129. <https://doi.org/10.3390/app14073129>.
- Tyagi, S. and Panigrahi, S.K. (2017), "An improved envelope detection method using particle swarm optimization for rolling element bearing fault diagnosis", *J. Comput. Des. Eng.*, **4**(4), 305-317. <https://doi.org/10.1016/j.jcde.2017.05.002>.
- Zhang, L., Wang, B., Liang, P., Yuan, X. and Li, N. (2023), "Semi-supervised fault diagnosis of gearbox based on feature pre-extraction mechanism and improved generative adversarial networks under limited labeled samples and noise environment", *Adv. Eng. Inform.*, **58**, 108814. <https://doi.org/10.1016/j.aei.2023.102211>.
- Zheng, X., Huang, Y., Xin, Y., Zhang, Z., Liu, W. and Liu, D. (2024), "Sparse measure of bearing fault features based on Legendre wavelet multi-scale multi-mode Entropy", *Comput. Elec. Eng.*, **116**, 109204. <https://doi.org/10.1016/j.compeleceng.2024.109204>.
- Zheng, X., Ye, Z. and Wu, J. (2022), "A CNN-ABiGRU method for gearbox fault diagnosis", *Int. J. Circuits Syst. Signal Pr.*, 440-446. <https://doi.org/10.46300/9106.2022.16.54>.
- Zhu, J., Aidong, D., Xing, L. and Li, O (2024), "Rolling bearing fault diagnosis based on multi-source information fusion", *J. Fai. Anal. Prevent.*, 1-13. <https://doi.org/10.1007/s11668-024-01935-5>.